A multi-sensor inference and data fusion method for tracking small, manoeuvrable maritime craft in cluttered regions

A multi-sensor inference and data fusion method for tracking small, manoeuvrable maritime craft in cluttered regions†

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Abstract

We present an inference and data fusion method for tracking maritime Fast Inshore Attack Craft (FIACs) using multiple sensors. The scenario addressed encompasses littoral, counter-piracy and maritime constabulary operations. The problem space is characterised by mixed sensor modalities, non-stationary and spatially-varying non-Gaussian clutter, intermittent observations and a high false alarm rate. Our method combines the Probability Hypothesis Density (PHD) filter for multi-target Bayesian inference with Generalised Covariance Intersection (GCI) for decentralised data fusion.

We outline the development and testing of our solution using Electro-Optic and radar observations of marine traffic in the Solent. These data are complemented by ground truth positional data of marine traffic including high-frequency positional estimates of two representative FIACs. Our system has been deployed both offline and in real time. We carry out a number of experiments designed to show the efficacy of the algorithms in representative scenarios. The performance of our algorithms is quantified using multi-target inference metrics. We show that the combination of PHD and GCI has many advantages over traditional inference and fusion methods, particularly in cluttered environments.

1. Introduction

A fundamental requirement of Intelligence, Surveillance and Reconnaissance (ISR) is target tracking and, in particular, the maintenance of tracks through highly cluttered environments. There are a number of recursive estimators whose effectiveness generally wanes with increasing number of targets, false alarm rate, non-linear target dynamics and clutter (see e.g. [1]). In any ISR situation, sensors may be co-located with information users or they may be provided by remote, off-board systems which communicate over a tactical network. The combination, or fusion, of information must be undertaken in a manner which combines the uncertainties inherent in each estimate while accurately reflecting the network topology (e.g. to account for loops and possible double-counting issues).

An example of a challenging tracking/fusion problem is provided by small fast boats, so-called Fast Inshore Attack Craft (FIACs), in the littoral environment. This problem is of a high priority for the Royal Navy, particularly in its counter-piracy and maritime

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constabulary operations. These craft have a small sensor cross section, and can execute sharp turns. A number of sensors in combination may be tasked to track these targets. In future operations such sensors may be hosted on-, or off-board, a diverse set of manned and unmanned platforms.

The focus of this paper is an advanced distributed tracking algorithm which has both theoretical and practical advantages over current solutions deployed against maritime littoral targets. We hypothesise that it will deliver improved accuracy in multi-target estimates as it is suited to extracting and integrating information in cluttered environments with intermittent observations and high false alarm rates. It may further be extended to any situation where there is a requirement to obtain a Common Operating Picture by fusing multiple geographically-distributed information sources to track multiple targets.

Our approach combines an efficient recursive Bayesian multi-object estimation algorithm known as the Probability Hypothesis Density filter with an adapted version of the Covariance Intersection (CI: [2]) fusion algorithm, extending CI beyond single object distributions and uncertainties approximated by Gaussians [3]. The PHD filter works by computing an intensity function which gives the expected number of targets at any region. By doing so, it removes the requirement to compute specific plot-track associations which can be error-prone and computationally expensive. Peaks in the intensity function, or, PHD, give the locations of the individual targets. The Random Finite Set (RFS) framework, which underpins the PHD filter, allows complex models of target signatures and clutter to be constructed. This enables information to be combined at a relatively low level and gives rise to improved tracking performance [5]. The generalisation of CI (GCI) facilitates the CI principle for general distributions through their exponential mixture densities (EMDs).

The goal of this study is to apply the PHD/GCI method, which has previously been proven on simulated data [4], to a representative maritime tracking scenario. In §2 we describe the theory behind the PHD filter, GCI-based fusion and their combination. Section 3 details the data and experiments used to test our algorithms with the analysis and results. We provide conclusions and recommendations in §4.

2. Mathematical formulation

In an abstract multi-target tracking scenario each sensor in a distributed network collects noisy, cluttered data from targets moving in the surveillance region and can communicate with neighbouring linked sensors only. Suppose at time, t, there are n_t targets defined collectively by a set of states, $\mathbf{X}_t = \{\mathbf{x}_{t,1} \ldots \mathbf{x}_{t,n_t}\}$. We collect m_t measurements in the observation space, denoted as $\mathbf{Z}_t = \{\mathbf{z}_{t,1} \ldots \mathbf{z}_{t,m_t}\}$. The object of Bayesian multi-target filtering algorithms is to estimate the posterior probability density of the target states conditioned on all observations made up until time t, $f_{t|t}(\mathbf{X}_t|\mathbf{Z}_{1:t})$. The uncertainties in $\mathbf{X}_t$ (caused by unknown target appearance and disappearance) and $\mathbf{Z}_t$ (which may include clutter and multiple detections per target), are modelled as random finite sets. The properties of $\mathbf{X}_t$ and $\mathbf{Z}_t$ are also well suited to the maritime multi-target tracking problem described in §1. Figure 1 gives a pictorial representation of the multi-target tracking problem.

2.1. *Inference: the Probability Hypothesis Density filter*

Mahler [5] shows that a mathematically sound derivation of $f_{t|t}(\mathbf{X}_t|\mathbf{Z}_{1:t})$ has to be carried out using finite set statistics. However, many of the operations scale factorially and cannot be implemented in practice. The value of the method, however, is that it leads to an efficient way in which multitarget tracking can be carried out using the first order statistical moment of $f_{t|t}(\mathbf{X}_t|\mathbf{Z}_{1:t})$, known as the Probability Hypothesis Density (PHD).

The PHD is defined as $D_{t|t}(\mathbf{x}|\mathbf{Z}_{1:t}) = \int \delta_{\mathbf{X}}(\mathbf{x}) f_{t|t}(\mathbf{X}_t|\mathbf{Z}_{1:t}) \delta\mathbf{X}$, where $\delta_{\mathbf{X}}(\mathbf{x}) = \sum_{w \in \mathbf{X}} \delta_w(\mathbf{x})$

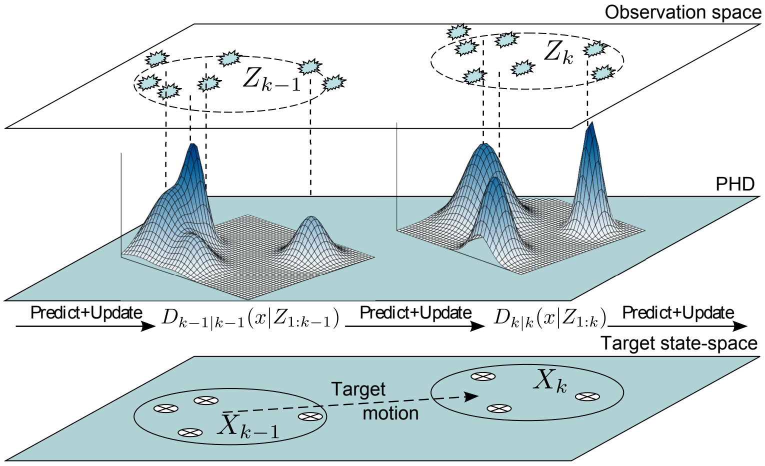

FIGURE 1. A representation of events in target state space (bottom) producing sensor measurements in an observation space (top) at times $k-1$ and k. The inference technique described in this paper propagates an intensity function, the PHD (middle panel), through the predict/update steps common to recursive Bayesian estimators. The integral of the PHD over a region χ yields the expected number of targets in χ.

is the dirac delta measure and w are the elements of X. Quite what the first order statistical moment is, and how it is derived is dealt with in detail in [6]. Crucially from our point of view, the integral of the PHD filter over any region χ in the state space $\mathbf{X}$ is

$$\int_{\chi} D_{t|t}(\mathbf{x}|\mathbf{Z}_{1:t})d\mathbf{x} = \nu_{t|t},$$

the expected number of targets in χ, whereas over the whole space it is the expected number of targets. In this study we realise PHD filtering using the Sequential Monte Carlo approach with an adaptive (target) birth density as described in [7].

2.2. *Fusion: Generalised Covariance Intersection*

Our goal is to track the targets using the information gathered by the network which has an arbitrary and time-varying topology unknown to the platforms. In order to fuse distributions from different platforms, the CI [2] approach has been generalised for multi-target densities, referred to as EMD since CI is attributed to Gaussian distributions [8],[3]. The resulting fusion algorithm constructs a new multi-target distribution from two posteriors, $f^0_{t|t}(\mathbf{X}_t|\mathbf{Z}^0_{1:t})$ and $f^1_{t|t}(\mathbf{X}_t|\mathbf{Z}^1_{1:t})$. We approximate the centralised estimate with an EMD such that $f_{t|t}(\mathbf{X}|\mathbf{Z}^0_{1:t} \cup \mathbf{Z}^1_{1:t}) \approx \tilde{f}_{t|t}(\mathbf{X}_t|\mathbf{Z}^0_{1:t}, \mathbf{Z}^1_{1:t})$ where

$$\tilde{f}_{t|t}(\mathbf{X}_t|\mathbf{Z}^0_{1:t}, \mathbf{Z}^1_{1:t}) = \frac{f^0_{t|t}(\mathbf{X}_t|\mathbf{Z}^0_{1:t})^{1-\omega} f^1_{t|t}(\mathbf{X}_t|\mathbf{Z}^1_{1:t})^{\omega}}{\int f^0_{t|t}(\mathbf{X}_t|\mathbf{Z}^0_{1:t})^{1-\omega} f^1_{t|t}(\mathbf{X}_t|\mathbf{Z}^1_{1:t})^{\omega} \delta\mathbf{X}_t}$$

and ω is a free parameter which is selected using an appropriate criterion, for example equality of the Kullback-Leibler divergence of the EMD with respect to the input distributions [9].

The fused distribution, owing to the nature of the EMD rule, prevents double-counting of information under unknown communication topologies (see [3]) and in return is sub-optimal compared to the centralised result. Explicit formulae for EMDs of RFS distributions have been given in [10] which derives methods for EMD fusion of PHD filters. It has been shown

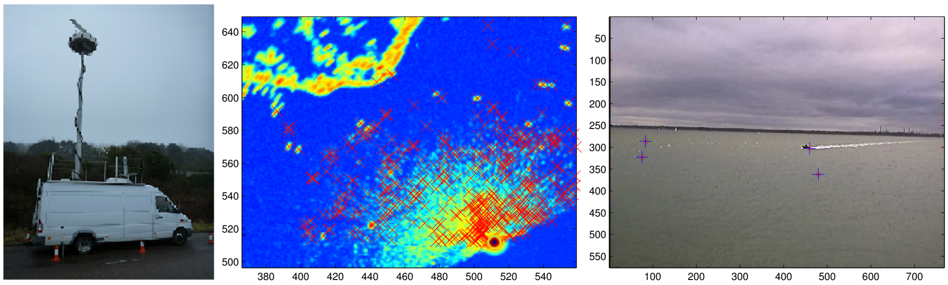

FIGURE 2. *Left:* The ISSD showing the radar and EO sensors *in situ* with the mast raised to $\sim$ 7m. *Centre:* Example raw radar image and sample detections (red crosses). *Right:* Example EO sensor capture and detections (blue crosses) based on a saliency map proposed in [12]. In the latter panels the axis units are pixels.

that the proposed approach is capable of significantly improving target localisation accuracy by exploiting the diversity in the information gathered by different platforms [11],[4].

3. Maritime testing and analysis

The PHD filter and GCI have previously been demonstrated in simulation [4]. Our goal is to apply the method to a representative above-water multi-sensor tracking problem.

3.1. *The data*

We gathered data from representative sensors in a realistic environment using the Integrated Sensor Suite Demonstrator (ISSD), a BAE Systems facility run by the Maritime Services division. The ISSD is a mobile maritime/anti-piracy-focussed sensor and data fusion demonstrator. It is suitable for harbour and coastal operations out to several tens of kilometres. The sensor suite comprise co-located navigational (Nav) radar, visual and IR sensors with a 360 degree field of vision, and supporting infrastructure. The sensor height is adjustable to 10m. Figure 2 shows the ISSD and examples of radar and EO data. The data were gathered in March 2013. Two representative Fast Inshore Attach Craft (FIACs) were contracted to play out a series of behaviours. The FIACs were instrumented with GPS data loggers which recorded the positions, and associated timings, of the FIACs at 10Hz.

Inference is undertaken on detections from each sensor individually and subsequently fused using GCI. The Nav radar processing chain is configured to output detections (i.e. processed returns from objects in the field of view: plots in radar signal processing terminology) via Campridge Pixel SPX$^{\mathrm{TM}}$software for ingestion by the radar PHD filter. The camera system provides imagery, so an algorithm based on the saliency map proposed in [12] is used to create detections which are then sent to the EO PHD filter. Filtering, fusion and visualisation operations are viewable live via a laptop computer added to the ISSD network.

3.2. *Experimental method and results*

We undertake experiments to demonstrate the efficacy of our algorithms in two main areas. Firstly, we test whether the PHD filter provides accurate localisation. Secondly, we test whether the GCI method further improves the multi-object estimation accuracy over single sensor PHD filters. We use the GPS-recorded positions of the FIACs as ground truth. To demonstrate fusion, we consider a radar and an EO PHD filter. Due to the uncertainties in EO calibration parameters, the EO pixel coordinates transformed onto the ground plane

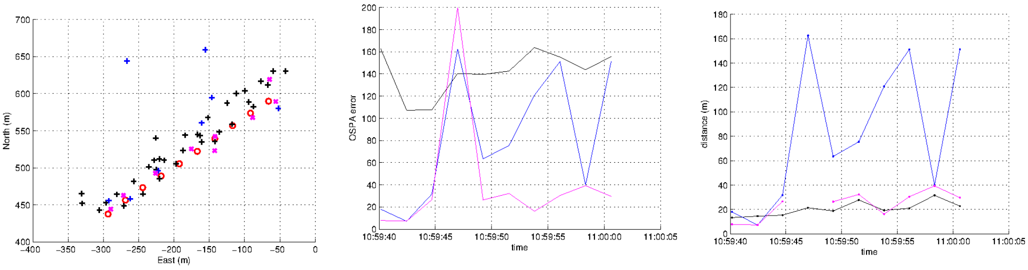

FIGURE 3. Results of performing the inference and fusion on radar and EO sensor feeds observing FIACs: (*left*) Target position obtained by GPS (red circles), state estimates from the PHD filter processing radar plots (black crosses) and the PHD filter processing EO detections (blue crosses) together with the estimates based on the GCI fused PHD (magenta crosses) for approximately 20s. (*centre*) The OSPA error of the radar filter (black), the EO filter (blue), and GCI fusion (magenta). (*right*) Euclidean position errors of those target estimates closest to the ground truth.

have high range uncertainty. Radar plots have large numbers of false alarms and multiple detections around the FIAC.

Figure 3 (left) shows multi-target estimates along with the GPS positions. We consider the set of PHD-filter-based target estimates and the GCI estimate that falls within 200m of the GPS position of the FIAC. The set of estimates based on the radar plot filter contain more than one target location in this region, due to multiple detections received around the target. The EO filter, on the other hand, leads to a single target estimate around the FIAC which is less accurate compared to the best radar estimate because of the relatively low range accuracy.

In order to assess the quality of these sets of target-estimates, we use the Optimal Sub-Pattern Assignment (OSPA; [13],[14]) which is a metric between two sets akin to the Euclidean distance between two real vectors. It provides a direct and consistent way to quantify the error between the multi-target estimate and the ground truth and is capable of capturing the errors in both the estimated number of objects and the location estimates.

Figure 3 (centre) shows the OSPA error of the multi-target estimates from the radar and the EO PHD filters and GCI fusion†. The GCI fusion provides a PHD which leads to a single target estimate around the target which improves upon the localisation accuracy of the EO estimate and the target number estimate of the radar filter. In this respect, GCI fusion provides a good compromise between accuracy in target localisation and target number estimation by incorporating the information from the more accurate radar and less cluttered EO sensors. This can be further verified by Figure 3 (right) in which we show the Euclidean distance errors of the estimates closest to the true target position. The radar filter exhibits the best localisation performance (black curve in Figure 3 (right)). Figure 3 (right, black) also shows that PHD filtering yields positional estimates accurate to $\sim$ 10m at $\sim$ 0.5km. This is comparable to current Doppler methods against single targets using X-band radar (see eg. [15]) and shows that PHD-filtering can improve target estimation for a simple Nav radar. Current practices for assessing tracking methods (e.g. [16]) require the formation of tracks; few, if any, operate directly on intensity functions. Future work will make a direct comparison of the PHD/GCI method with current tracking methods by forming tracks from the GCI-fused intensity function.

† The exponent and cut-off parameters of the OSPA metric [13] are selected as 1 and 200 respectively.

4. Summary and conclusions

We have demonstrated distributed inference and fusion in a maritime littoral environment. Our method employs Probability Hypothesis Density filters for inference and Generalised Covariance Intersection to fuse data from radar and EO sensors. The intent is to improve capability in the tracking of Fast Inshore Attack Craft. Targets such as these are a high priority for the Royal Navy in its counter-piracy and maritime constabulary operations. Tracking, inference and fusion is complicated by spatially-varying non-Gaussian clutter, intermittent observations and a high false alarm rate.

We have gathered development and test data using co-located radar and EO sensors using a BAE Systems Maritime Services demonstration platform. The filtering and fusion algorithms have been demonstrated in real-time. Experimental data was also gathered to prove the algorithm.

We have described experiments to show the efficacy of our method. We show that single sensor PHD filtering in radar gives comparable location accuracy to current methods using Doppler techniques. The GCI fusion of EO and radar detections improves the multi-object state estimation in cluttered environments by integrating complementary information. Future work will test improvement in tracking ability by comparing tracks formed from the GCI-fused intensity function with tracks formed from unfiltered plot streams.

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